White Paper: Estimating Salinity Effects Due to Climate Change on the Georgia and South Carolina Coasts

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INTRODUCTION

This White Paper describes highlights from a report for Water Research Foundation (WaterRF) project 4285 having the same title, which investigated ways for coastal utilities to assess the risk to their water supplies if climate change and seal-level rise. In addition to WaterRF, the project was co-sponsored by Beaufort-Jasper Water and Sewer Authority (BJWSA) and the National Oceanic and Atmospheric Administration. It was performed as collaboration among Advanced Data Mining International, LLC (ADMi), the U.S. Geological Survey (USGS), the University of South Carolina (USC), and the South Carolina Sea Grant Consortium (Sea Grant).

There are many theories of causes behind climate change but little disagreement that it is happening. Climate change and sea-level rise will alter hydrologic patterns, resulting in changes in salinity intrusion dynamics along coastal rivers where many utility intakes are located. The increase in the degree of saltwater intrusion along the Georgia and South Carolina coasts during the Southeast's record-breaking drought from 1998 to 2002 illustrated how climate change and sea-level rise increase the threat to freshwater estuarine intakes, showing the need of utilities for reasonable estimates of future changes in the frequency, duration and magnitude of salinity intrusion near their water intakes. The objectives of this project were to:

- Develop an approach, or template, that coastal utilities can use to evaluate the threat from climate change and sea-level rise to their freshwater estuarine intakes;
- Demonstrate the effectiveness of the approach by applying it to two separate estuarine systems in Georgia and South Carolina.

ADMi and the USGS had previously developed specific-conductance models of the Lower Savannah River and Grand Strand region estuarine systems (Conrads et al. 2006, Conrads and Roehl 2007), in which reside two and three municipal freshwater intakes, respectively. The models convert inputs that primarily represent freshwater streamflow and sea level into predictions of specific conductance at several locations. In both systems it was found that the relationships between sea level, freshwater streamflow, and salinity intrusion are complex and nonlinear, and that weather extremes such as droughts and increased sea levels brought by hurricanes can produce large intrusion events. It is possible that the negative impacts of climate change on utilities could be exacerbated by increasing inter-annual climate variability (specifically, more droughts), and increasing fresh water demands from upstream farms, industries and water utilities.

The Savannah River estuary is a deltaic system that branches into a series of interconnected distributary channels (Figure 1). Among the area's most important resources are the Savannah National Wildlife Refuge and the nearby port terminals of the Savannah Harbor.

Two municipal water intakes are located in the freshwater portion of the upper estuary. The City of Savannah maintains an intake on the Abercorn Creek tributary, approximately 1 mile upstream of USGS gage 02198840, which provides specific conductance and water level measurements. The intake for the Beaufort-Jasper Water and Sewer Authority is located at a canal off of the Savannah River approximately 15.5 river miles upstream of 02198840.

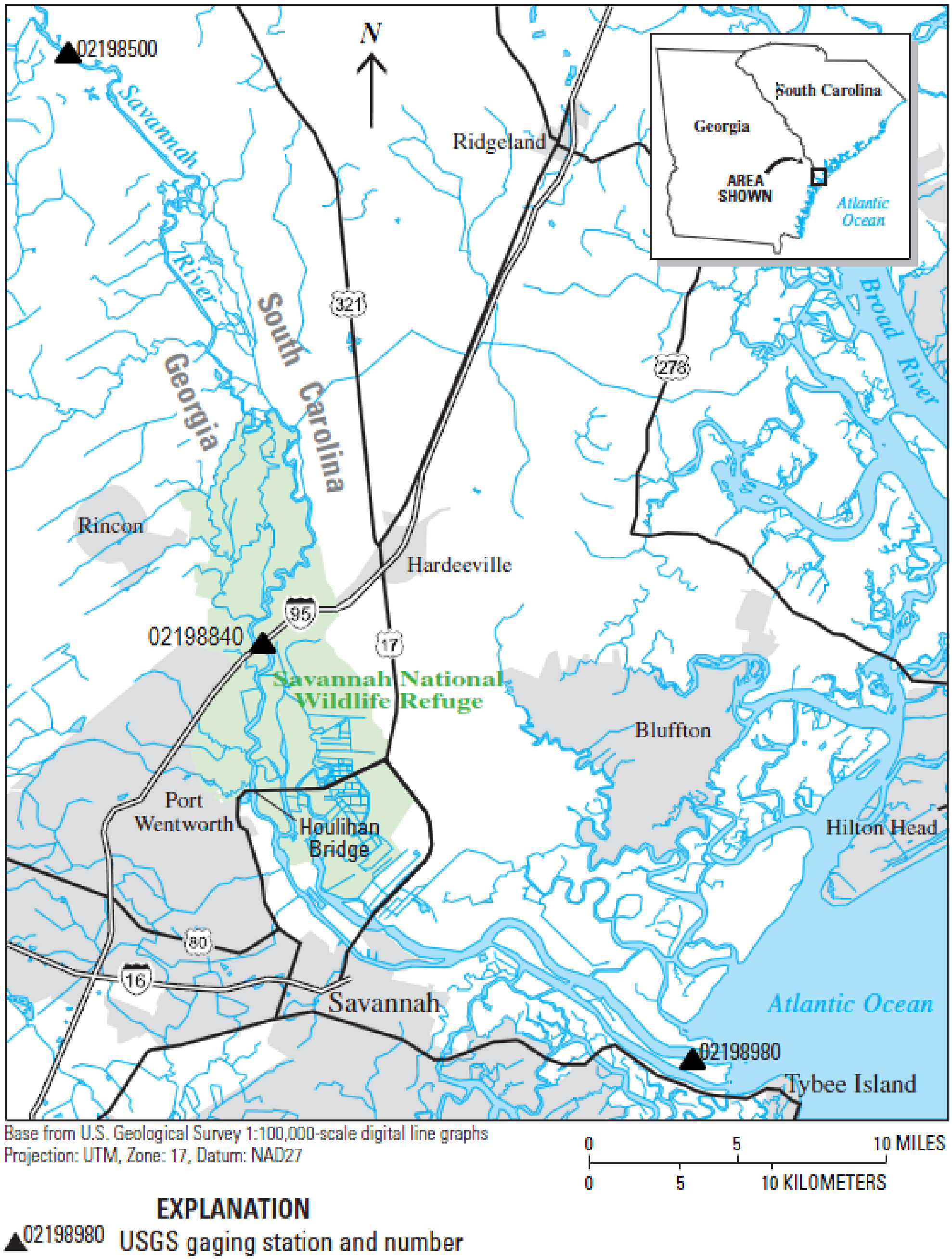

Figure 1. The Lower Savannah River.

The salinity model used in this project was originally developed to evaluate the impact of a proposed deepening of the harbor on the Refuge and other areas, and is named the Savannah

River Model-to-Marsh (M2M). The USGS gaging stations on the Savannah River near Clyo, Ga. (02198500) and at Fort Pulaski (02198980) provided the data representing the model's input boundary conditions.

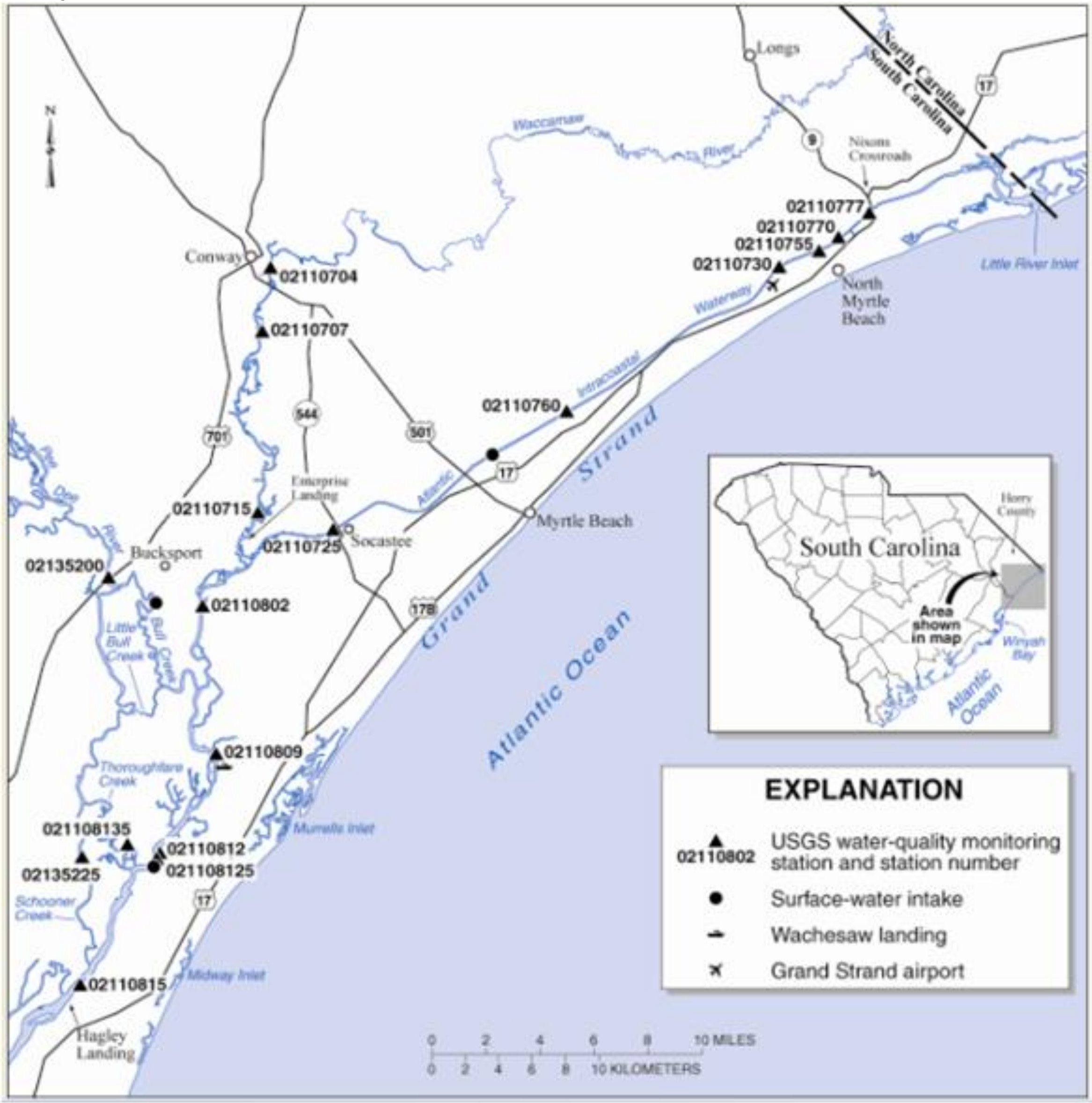

Figure 2. Lower Pee Dee River, AIW, and Waccamaw River estuarine system.

Figure 2 shows the second study area, which is the estuarine system composed of the Lower Pee Dee River, the Waccamaw River tributary, and the Atlantic Intracoastal Waterway (AIW). The Pee Dee River, named the Yadkin River in North Carolina, flows through several hydroelectric facilities, the last being approximately 15 miles upstream from the state border. The reach of the AIW from just south of Little River Inlet to just north of Hagley Landing provides freshwater for the coastal communities of the Grand Strand. Three municipal surface-water intakes are in the tidal, freshwater portions of the system. During a drought from 1998 to 2002, salinity intrusion forced the intake near USGS gage 021108125 to close until increased streamflow moved the freshwater-saltwater interface downstream.

Figure 2 also shows the U.S. Geological monitoring sites on the Waccamaw River and AIW that provided much of the data used to develop the specific-conductance model, which is named the **P**ee Dee **R**iver and Atlantic **I**ntracoastal Waterway **S**alinity Intrusion **M**odel (PRISM). The model was developed to support the process of the relicensing of the hydroelectric facilities by the Federal Energy Regulatory Commission, which occurs at 50-year intervals.

APPROACH

M2M and PRISM are actually decision support systems (DSS) that integrate several empirical specific-conductance sub-models, the real-time databases needed for running simulations, graphical user interfaces (GUI), and streaming graphics. The DSSs are Microsoft Office Excel™ applications that are easily distributed and immediately usable by all water-resource managers and other stakeholders. Deploying the models in this form provides resource managers of varying computer skills with equal access to the scientific knowledge is needed for them to make the best possible decisions (Roehl, Conrads, and Daamen 2006).

The original DSSs were redeveloped using additional field data, and modified to allow users to modulate the sea level input and unregulated flows. The modified DSSs were renamed M2M-2 and PRISM-2. The data used to develop the M2M sub-models and run simulations spans 11 years from 1994 through 2005. The PRISM-2 data spans 14 years from 1995 to 2009. Both data sets incorporate a broad range of climate and sea level behaviors, including record droughts, high rainfall periods of El Niño climate periods, and hurricanes, which can greatly increase sea levels. Developing the empirical sub-models from this range of data makes them more applicable to studies involving climate change and sea-level rise scenarios.

The sub-models were developed using multi-layer perceptron (MLP) artificial neural network (ANN) models which are commonly used for process engineering applications (Jensen 1994). They synthesize nonlinear functions to fit multivariate data, and offer significant advantages in modeling estuary hydrology versus traditional mechanistic modeling codes, including prediction accuracy, speed of development, execution speed, and breadth of deployment options (Conrads and Roehl 1999; Conrads and Greenfield 2008).

Forecasting the Impact of Climate Change at an Intake

Estuary salinity variability is largely driven by streamflow and tidal water-levels, and climate change will affect both. To forecast future streamflows, global circulation, regional circulation, watershed runoff, and salinity intrusion models need to be integrated (Figure 3). Global circulation models (GCM) make large scale (>250 square kilometer grid) estimations of precipitation and temperature conditions for various carbon emission scenarios. These scenarios are typically 100-year projections to the future. To generate precipitation and temperature predictions for a watershed (approximate 12 square kilometer grid), the GCMs are coupled to regional circulation models that generate regional precipitation and temperature predictions, which are then input to a watershed model. The watershed model then predicts the streamflow inputs to an estuary model such as PRISM-2.

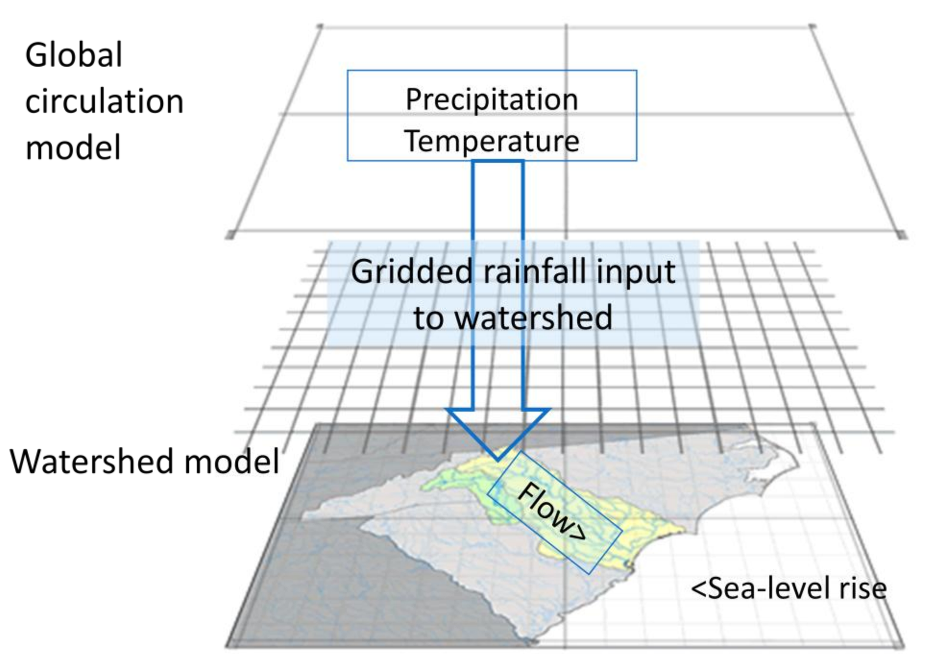

Figure 3. Conceptual approach for modeling the effects of climate change on salinity intrusion.

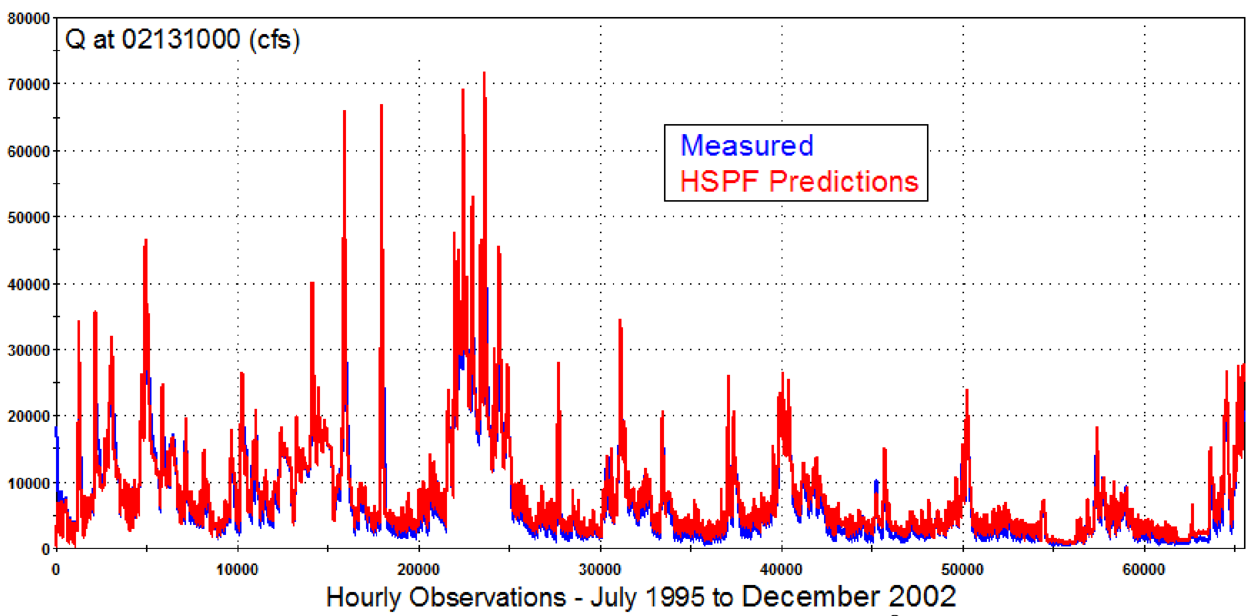

Figure 4. Measured and HSPF-predicted Q at USGS 02131000. R^2=0.85.

The Pee Dee Basin streamflow forecast was generated by USC and Sea Grant for the years 2055-2069, 60 years from the start of the PRISM-2 study period. The forecast was made using the Hydrologic Simulation Program-Fortran (HSPF) watershed model from the U.S. Environmental Protection Agency, and the ECHO-G GCM (Legutke and Voss, 1999). It was used to predict future Pee Dee Basin streamflow (Q) from a climate forecast by ECHO-G for input to PRISM-2. The HSPF application was calibrated using approximately 30 years of historical climate and Q data. PRISM-2 uses Q inputs corresponding to five gaging stations. Figure 4 compares predictions made by the HSPF application with the measured Q at USGS 02131000 on the Pee Dee River.

There are many existent GCMs, four of which were evaluated. ECHO-G was chosen because it predicted historical low flow conditions most accurately when coupled with the HSPF application. To predict future flows, ECHO-G was run with the A2 future carbon emissions scenario, which assumes that nations will continue to pursue their interests individually rather than cooperate in dealing with climate change (IPCC 2000). Alternative emission scenarios cause global circulation models to forecast different climates.

RESULTS

This section focuses on showing ways that large amounts of seemingly complex data can be reduced to forms that are readily understood by resource managers. It should be noted that the M2M-2 output is in practical salinity units (psu), and PRISM-2 outputs specific-conductance (SC) in micro-Siemens per centimeter (μS/cm). The upper salinity limit for drinking water is 0.5 psu, or approximately 1,000 μS/cm.

For the Lower Savannah River, Figure 5 shows the measured salinity at USGS gage 02198840 with the freshwater Q at 02198500 for the 11-year study period. Figure 5 also shows the predicted salinity when historical input data is used, which is sufficiently accurate to largely obscure the measured values. At low Q, salinity spikes appear at 28-day intervals, coincident with the new moon and indicating the role of tidally-driven sea levels in intrusion events. Figure 6 shows a detail of simulation results for three scenarios – historical Q (ΔQ= 0%) with zero sea-level rise (SLR) (same as the predictions in Figure 5), ΔQ= 0% with a 1.0 ft SLR, and ΔQ= -10% with a 1.0 ft SLR. The detail shows that a 1.0 ft SLR causes spikes to appear and that their magnitude and duration increase with a Q decrease.

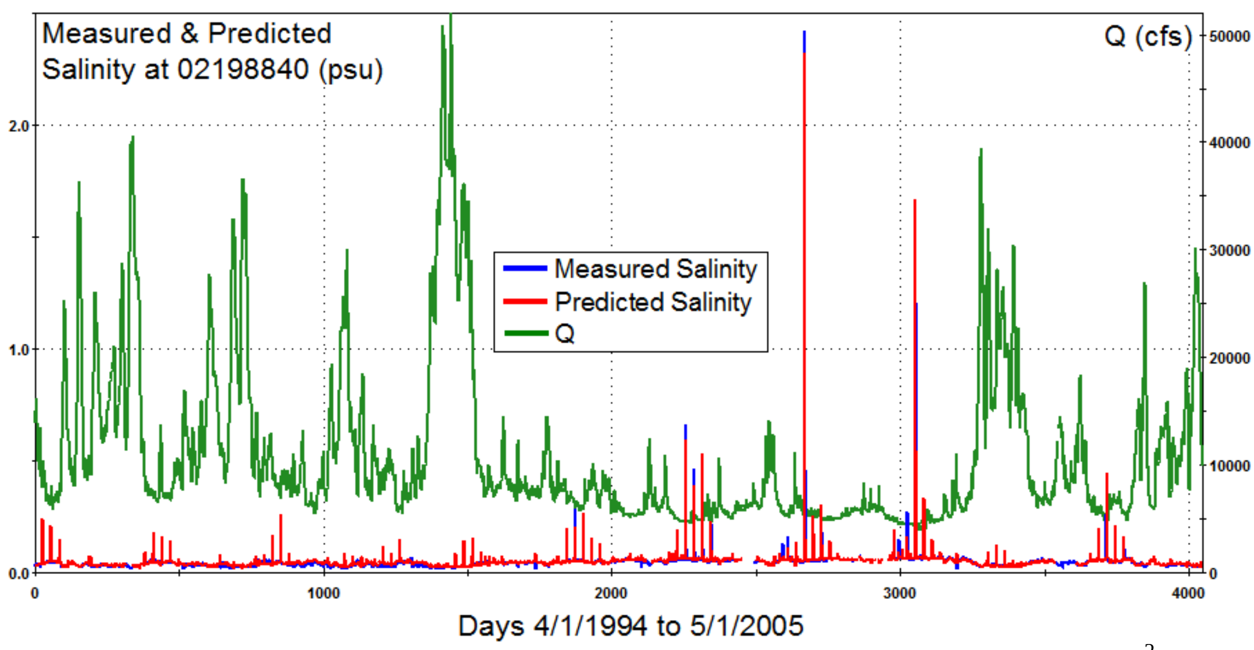

Figure 5. Measured and predicted salinity at USGS 02198840 with Q at 02198500. R^2=0.81.

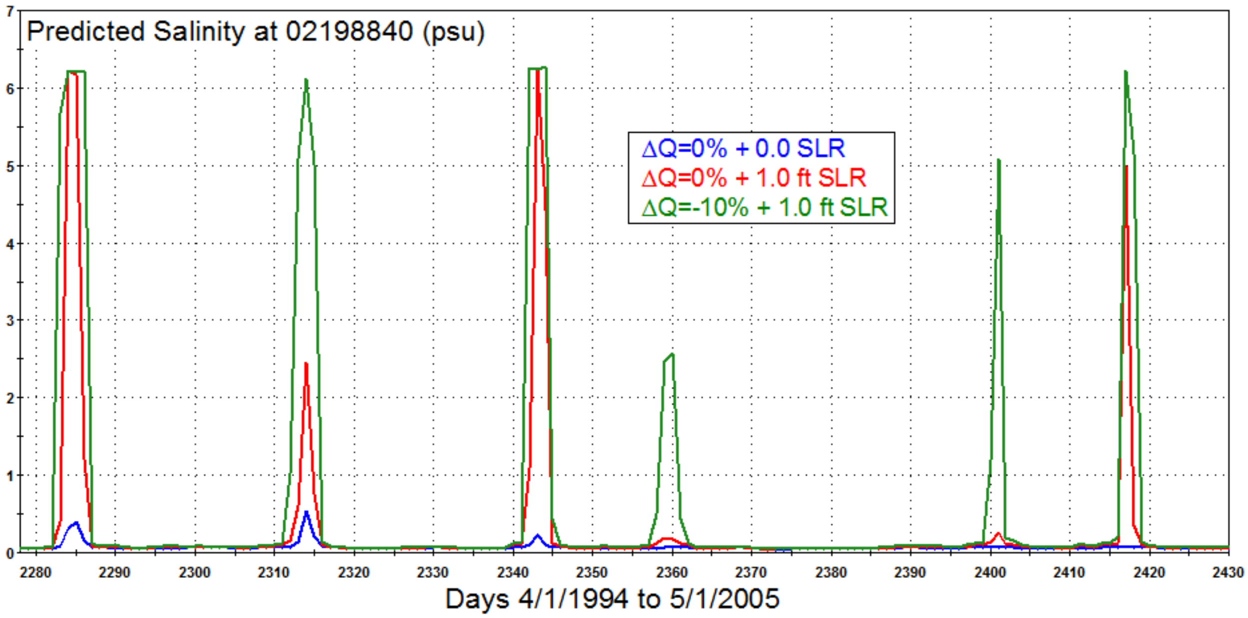

Figure 6. Detail of simulation results for three scenarios.

ΔQ / SLR (ft)	%days > 0.5 psu						
	0.0	0.5	1.0	1.5	2.0	2.5	3.0
0%	0.2	0.5	1.4	3.1	5.9	9.7	13.6
-5%	0.3	0.7	1.8	3.9	7.0	11.2	15.4
-10%	0.4	0.9	2.3	4.6	8.6	12.5	17.7
-15%	0.5	1.4	3.0	5.8	10.0	14.5	20.0
-20%	0.6	1.7	3.8	7.1	11.4	16.8	22.0
-25%	1.0	2.2	4.7	8.7	13.3	19.3	24.1

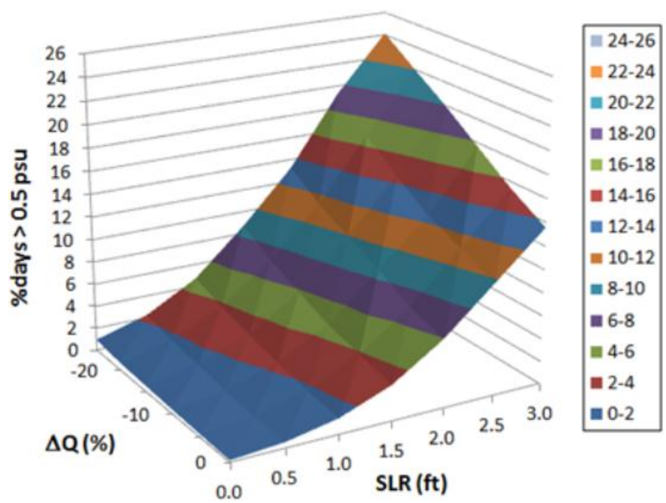

Figure 7. Percentage of days that predicted salinity > 0.5 psu.

Forty-two (42) scenarios were run in which SLR and Q were modulated parametrically. The output data were processed to calculate the percentage of study period days (%days) at which the salinity exceeded 0.5 psu. Figure 7 shows the results in tabular form and as a 3D surface. The table indicates that SLR increases the percentage more than Q reduction. For example, at ΔQ= 0% and SLR= 3.0 ft., %days= 13.6. At ΔQ= -25% and SLR= 0 ft., %days is only 1.0. The surface shows that %days increases linearly as ΔQ becomes more negative, and exponentially with increasing SLR. The combined effect is that %days increases much more per decrement in ΔQ at high SLR than at low SLR. For example, at SLR= 0 ft., the %days increases only slightly as ΔQ decreases from 0 to -25%. At SLR= 3 ft., the percentage increases much more as ΔQ decreases to -25%. Similarly, at ΔQ= 0 ft., %days increases less as SLR increases from 0 to 3.0 ft than at ΔQ= -25%. Given that the details of how climate change and SLR will evolve are uncertain, the kind of results shown in Figure 7, which are derived from a predictive model that was developed from a large and widely ranging data set, are perhaps the most credible type of planning data available to resource managers in coastal areas.

For the Waccamaw River, Figure 8 shows the measured SC at USGS gage 021108125 with Q for the 14-year study period. Here Q is aggregated from streamflows measured at five upland gages. The measured SC starts at day 2,305. Also shown is the SC predicted by the ANN sub-model when historical input data is used. Three prolonged periods of high SC appear in the vicinities of days 2,300, 2,600, and 4,400, which coincide with periods of low Q. It is clear that the nature of salinity intrusion is very different from that at the 02198840 gage on the Savannah River (Figure 5), suggesting that details of the process physics that cause behaviors of interest can vary greatly location-to-location, and that it is critical that predictive models used as planning tools need be customized for each location.

Salinity intrusion occurs when two of the following three conditions are met - low streamflow, high tidal range, and high mean sea-levels. In the Savannah River example, the salinity spikes in Figure 5 are of short duration and occur at 28-day intervals when Q is low and the gravitational forcing of the moon causes the tidal range to be high. High mean sea levels just increase the magnitude of the spikes. In the Waccamaw River example, the intrusions shown in Figure 8 are less periodic and of longer duration because the tidal range is less influential than streamflow and sea level.

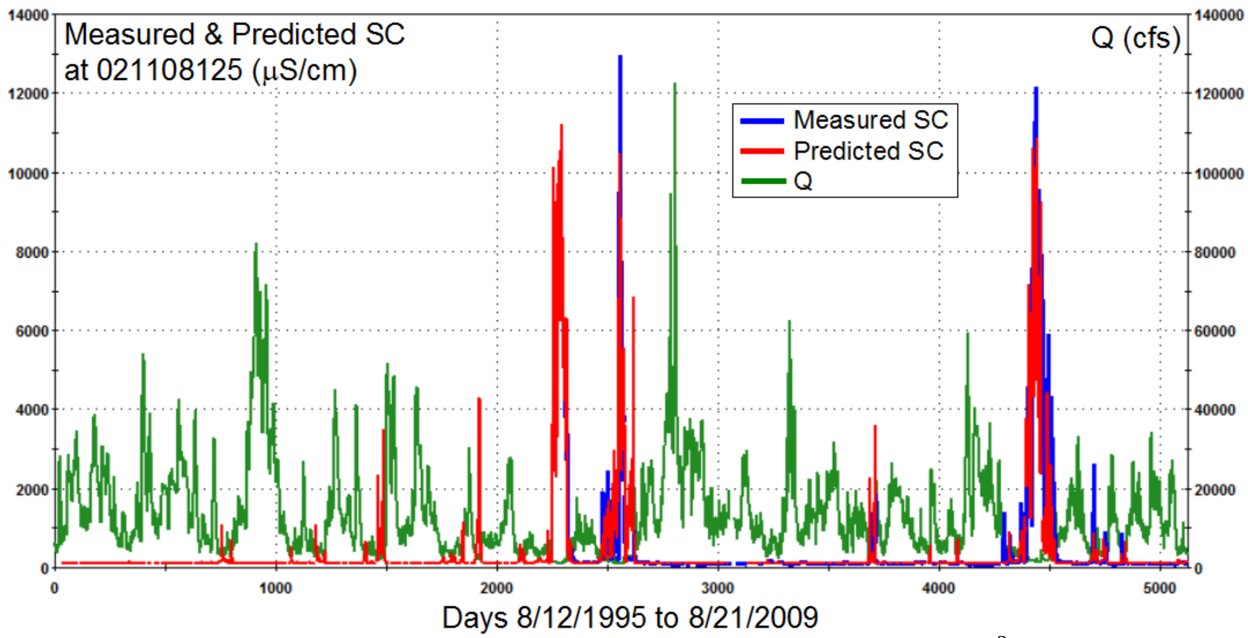

Figure 8. Measured and predicted SC at USGS gage 021108125 with Q. R^2=0.86.

Figure 9 shows simulation results for three scenarios – (1) historical Q (ΔQ= 0%) and sea level (same as the predictions in Figure 8); (2) ΔQ= 0% and sea level + 1.0 ft SLR; and (3) the ECHO-G/HSPF forecast Q with historical sea level + 1.0 ft SLR. The simulation period of (1) and (2) is 1995-2009, and 2055-2069 for (3). Scenario (2) indicates that the increased SLR increases the magnitude, duration, and frequency of SC spikes. Scenario (3) generally shows spikes occurring at times that are different from the first two scenarios, and are of shorter duration.

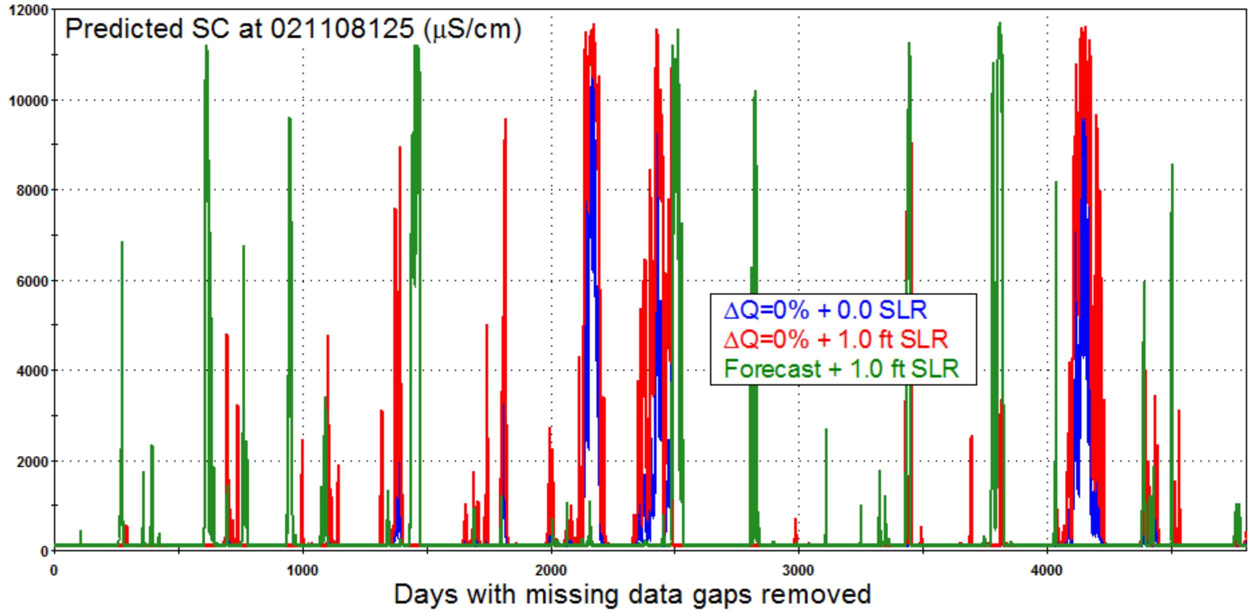

Figure 9. Simulation results for three scenarios.

ΔQ/SLR (ft)	%days > 1,000 µS/cm 0.0	0.5	1.0	1.5	2.0	2.5	3.0
0%	5	8	11	14	18	20	23
-5%	6	9	12	16	19	22	25
-10%	7	10	13	17	20	23	26
-15%	8	11	15	19	22	25	28
-20%	9	15	17	20	23	27	30
-25%	10	14	18	22	25	29	33

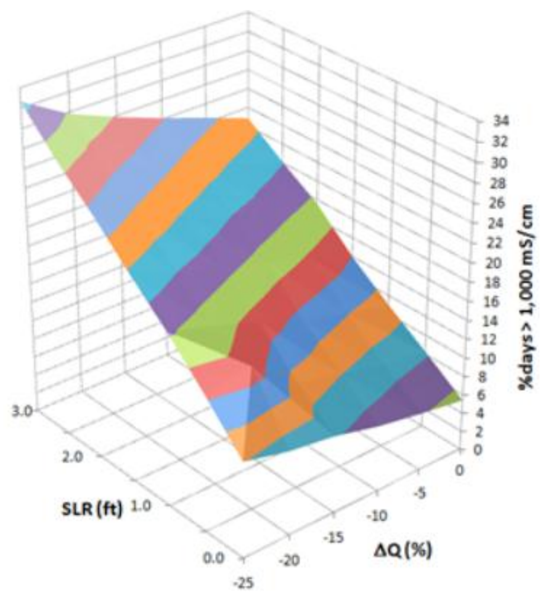

Figure 10. Percentage of days predicted SC exceeds 1,000 µS/cm.

Like the above Savannah River analysis, 42 Q/SLR scenarios were run to predict SC at 021108125, and the percentage of study period days (%days) at which the predicted SC exceeded 1,000 µS/cm was calculated (Figure 10). Similarly to the 02198840 gage (Figure 7), SLR affects %days more than ΔQ; however, the surface is more planar, such that the effect of ΔQ is relatively constant with increasing SLR. Figure 11 shows the number of predicted intrusion events when the predicted SC exceeds 1,000 µS/cm for 7 consecutive days. This type of information indicates how frequently an intake might be inundated for extended periods, a major concern for utilities with limited source or storage options.

ΔQ/SLR (ft)	# 7-day 1,000+ µS/cm Events						
	0.0	0.5	1.0	1.5	2.0	2.5	3.0
0%	10	19	24	37	52	53	56
-5%	14	19	29	42	54	53	61
-10%	16	22	33	53	54	57	68
-15%	19	26	40	54	54	62	71
-20%	19	32	48	53	58	68	73
-25%	21	36	54	53	64	72	76

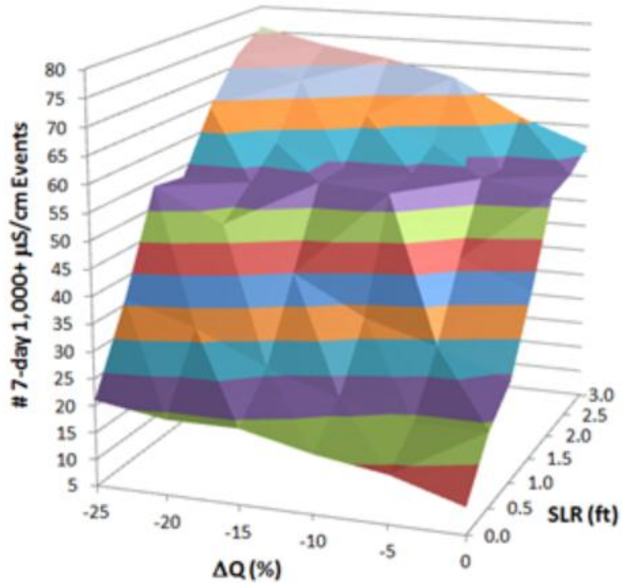

Figure 11. Predicted number of events when the SC > 1,000 µS/cm for 7 consecutive days.

Table 1 compares the percentages of study period days (%days) when the SC exceeded 1,000, 2,000, and 3,000 µS/cm for three cases, namely historical SC, SC predicted from historical Q and sea level, and SC predicted from ECHO-G/HSPF Q and historical sea level. The %days of the single historical SC scenario are comparable to the two prediction scenarios. The lower %days for the ECHO-G/HSPF Q scenarios relative to the SC-predicted-from-historical-inputs scenarios are consistent with the above observations about Figure 9.

Table 1. Percentages of days when the SC > 1,000, 2,000, and 3,000 µS/cm.

	%days > 1,000, 2,000, and 3,000 µS/cm								
	historical SC			historical Q			ECHO-G/HSPF Q		
SLR (ft)	1,000	2,000	3,000	1,000	2,000	3,000	1,000	2,000	3,000
0.0	7	4	4	5	4	3	4	3	2
1.0				11	9	7	7	5	4
2.0				18	15	13	11	9	7
3.0				23	20	19	15	13	11

APPLICATIONS / RECOMMENDATIONS

The general problem for water resource managers that want to plan for climate change AND sea-level rise is figuring out how it might specifically affect "their" resources. The problem is made seemingly intractable because the details about what, when, and how much are unknowable with any certainty. This project has demonstrated a pathway to be taken that produces tools that are straightforward to use and should be reliable if their limitations are respected. The tools are tables and graphics that predict how often and for how long intakes will be inundated by salinity intrusion for any reasonable combination of freshwater flow change or sea-level rise. There are similar analogs when the water resources are inland, such as lakes, streams, and groundwater, and the forcing includes anthropogenic demand.

The two essential elements that were extensively leveraged for both the Savannah and Waccamaw River intakes were:

1. *Long-term time series data* - that captured a broad range of complex natural system behaviors, and inherently span much of the change that experts predict will come with climate change, as manifest in the ECHO-G A2 scenario.
2. *Predictive models* - that accurately represent the process physics captured by the long-term time series data.

#1 is of fundamental importance and obviously time-consuming to obtain if not already in hand. #2 can be developed at any time so long as a reasonable amount of data is available, and models are readily updated when new data becomes available. For some systems, such as estuaries, empirical models like those used here can be developed more quickly and be more accurate than conventional mechanistic modeling codes. Ideally, 1 and 2 are already available and merely need to be exercised to produce the tables and graphics needed by resource managers to begin assessing risk and planning for climate change.

REFERENCES

Conrads, P.A. and E. A. Roehl. 1999. Comparing Physics-Based and Neural Network Models for Predicting Salinity, Water Temperature, and Dissolved Oxygen Concentration in a Complex Tidally Affected River Basin, In Proc. of the South Carolina Environmental Conference, Myrtle Beach, SC.

Conrads, P.A., E.A. Roehl, R.C. Daamen, and W.M. Kitchens. 2006. Simulation of Water Levels and Salinity in the Rivers and Tidal Marshes in the Vicinity of the Savannah National Wildlife Refuge, Coastal South Carolina and Georgia. U.S. Geological Survey Scientific Investigations Report 2006-5187.

Conrads, P.A., and E.A. Roehl. 2007. Analysis of Salinity Intrusion in the Waccamaw River and Atlantic Intracoastal Waterway near Myrtle Beach, South Carolina, 1995–2002. U.S. Geological Survey Scientific Investigations Report 2007–5110.

Conrads, P., and J. Greenfield. 2008. Effects of Reduced Controlled Releases from Lake Thurmond on Salinity Intrusion in the Lower Savannah River Estuary. In Proc. of the South Carolina Water Resources Conference. Charleston, SC.

Conrads, P.A., E.A. Roehl, R.C. Daamen, and J.B. Cook. 2012. Estimating Salinity Intrusion Effects Due to Climate Change on the Georgia and South Carolina Coasts, 1995-2009. U.S. Geological Survey Scientific Investigations Report 2012–xxxx (to be published).

IPCC (Intergovernmental Panel on Climate Change). 2000. Special Report on Emissions Scenarios.:IPCC.

Jensen, B.A. 1994. Expert Systems - Neural Networks: Instrument Engineers' Handbook (3^{d} ed.). Radnor, PA.:Chilton.

Legutke, S. and R. Voss. 1999. The Hamburg Atmosphere-Ocean Coupled Circulation Model ECHO-G. Technical Report No. 18, German Climate Computer Centre (DKRZ), Hamburg.

Roehl, E.A., P.A. Conrads, and R.C. Daamen. 2006. Features of Advanced Decision Support Systems for Environmental Studies, Management, and Regulation. In Proc. of the International Environmental Modeling and Software Society Summit. Burlington, VT.